Use of Data Envelopment Analysis in an Evaluation of the Efficiency of the DEEP Program for Economic Education

Arthur M. Diamond, Jr., and Jeanette N. Medewitz

Since 1983, the Joint Council on Economic Education (JCEE) has expanded and enhanced its Developmental Economic Education Program (DEEP), which is aimed at achieving major improvements in the economics literacy of high school students by encouraging and training teachers and providing them with supplementary educational materials for high school economics classes (Brenneke et al. 1988). Recent efforts to test the effectiveness of DEEP have produced mixed results. Some studies, using standard ordinary least squares (OLS) production-function analysis, have found that the coefficient of a DEEP dummy variable is positive and statistically significant when the dummy variable is entered as an independent variable in the production function (Walstad and Soper 1988; Rhine 1989). Another study, using OLS production-function analysis that takes account of selection bias, has found that the coefficient of a DEEP dummy variable is not statistically significant (Becker and Walstad 1990).

We used the National Assessment of Economic Education (NAEE) data set collected by the JCEE, from funding provided by the J. Howard Pew Freedom Trust. The data set has a rich array of educational input variables and has a well-validated economic literacy test as an output measure. We used data envelopment analysis (DEA) to determine whether DEEP high school classes use resources more efficiently than non-DEEP classes. Efficient decisionmaking units, as defined in DEA, are those entities without slack; that is, they could not produce any more output with a given set of inputs. However, they are not necessarily economically efficient in the sense of using the least-cost set of inputs to produce a given output. We were thus measuring technical efficiency, which is a necessary, but not sufficient, condition for economic or allocative efficiency. Although DEA has never been applied to measure the efficiency of economic education programs, it has been used to test the efficiency of other educational programs (Charnes,

---

Arthur M. Diamond, Jr., is an associate professor of economics and Jeanette N. Medewitz is an assistant professor of finance at the University of Nebraska at Omaha. The authors are grateful for comments from Donald Baum, William E. Becker, William H. Greene, David Levy, Edwardo Rhodes, Sherwin Rosen, and David Thomas. They are also grateful to the Joint Council on Economic Education for providing the data and to the J. Howard Pew Freedom Trust, Inc., for funding collection of the data. Research assistance was ably provided by Teresa Olsen.

Cooper, and Rhodes 1981) and has also been applied to measure the efficiency of educational decisionmaking units (e.g., Charnes et al. 1981; Bessent et al. 1982; Bessent et al. 1983).

METHOD

The most useful efficiency measures for guiding policy would be those that informed us which production technologies and input combinations produced the output at minimum cost. Production at minimum cost is known as "economic efficiency." However, economic efficiency cannot always be determined with available data: information on the cost of inputs is often not available, especially in nonprofit activities like education. In such circumstances, it still may be useful to calculate technical efficiency. Bringing all decisionmaking units (DMUs) to the technical efficiency frontier is desirable, even if we cannot determine which point on the frontier is the economically efficient point.

The estimation of production functions by multiple regression or maximum-likelihood estimation is the most common technique within economics for determining the technical efficiency of a DMU. In the simplest approach, DMUs with positive residuals are judged efficient, whereas those with negative residuals are judged inefficient. Strictly speaking, to view positive residuals as indicating an efficient DMU is inconsistent with the notion that the estimated production function represents a frontier. The literature on stochastic frontier estimation that is associated with the work of Aigner, Lovell, and Schmidt (1977; also Greene 1980a, 1980b) attempted to address this problem by supposing that the error term in a production function can be decomposed into two parts, one representing stochastic error and the other inefficiency. Aigner et al. suggested a specification for estimating the components, although the separation is not successful for data sets of fewer than one hundred observations. (Whatever the other merits of the approach, this problem was sufficient to rule it out for our study because our data set contained students aggregated into forty-six high school classes.)

Banker and Maindiratta (1988) in their recent *Econometrica* article, showed that the efficiency values calculated in DEA constitute a tightest upper bound on the technical efficiency value. Grosskopf (1986) viewed stochastic frontier estimation and DEA as two alternative developments of ideas that originated with Farrell (1957). Grosskopf noted that the parametric approach (stochastic frontier estimation) has been developed mainly by economists, whereas the nonparametric approach (DEA) has been left to those in operations research. The main problem that economists associate with DEA is the incomplete knowledge of the statistical properties of the estimates. In particular, the worry is that we know too little about the consistency of the estimates. Grosskopf responded by showing how the restrictiveness of reference technology affects the bias of the estimates. He showed that, in general, the more restrictive the reference technology, the lower the measured efficiency values will be. He claimed that parametric models will also be affected by the restrictiveness of the reference technology, but that, in addition, their results will be greatly affected by the choice of error structure. His conclusion, stated at the outset of his article, was that "the value of the linear programming approach to measuring efficiency has been underestimated by economists, . . ." (1986, 501).

DEA has significant advantages over the usual method. First, it is not sensitive to the choice of functional form. Theoretical considerations indicate that DEA results on the efficiency or inefficiency of DMUs will be robust under DEA model changes (Banker et al. 1989, 9; Ahn, Charnes, and Cooper 1988; Charnes and Zlobec 1990). The second advantage of DEA is that it does not make the assumption that all DMUs are using the same technology, but instead evaluates the efficiency of a DMU relative to a group of similar DMUs. The third advantage is that DEA readily incorporates the existence of multiple outputs.[1]

DEA does have some disadvantages, but several of these are shared with the common technique of estimating production functions via multiple regression, namely, that the measure of efficiency depends on the set of DMUs included in the analysis and that technical efficiency is measured rather than economic efficiency. In addition, it is common in DEA (as we shall see in the present application) to find that many DMUs are evaluated as being efficient. The likelihood of this result increases with the number of inputs used. In multiple regression, however, we have a similar problem: that the addition of independent variables in the regression increases the R^2 value. In either technique, parsimony in the inclusion of inputs (or independent variables) is desirable.

Several studies have estimated production functions for economic education (for examples using DEEP as an independent variable, see Becker and Walstad 1990; Heath 1989; Rhine 1989; Walstad and Soper 1988). The only study of which we are aware that made use of any linear programming techniques was by Miller (1982). However, Miller only examined which inputs were being underused in a single institution. He did not obtain measures of efficiency, nor did he compare the economic efficiency of different programs (such as DEEP and non-DEEP). As far as we are aware, our study represents the first application of DEA to measure the efficiency of DMUs in economic education and to measure the efficiency of programs in economic education.

As a basis for comparison with the results of DEA, we first estimated standard production functions. In addition to a simple linear production function and the traditional Cobb-Douglas form, we also estimated the transcendental production function, which represents one way to generalize the Cobb-Douglas form (Intriligator 1978, 279). The functional form of the transcendental production function is

$$\begin{aligned}\ln y = {} & \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \beta_4 \ln x_4 + \beta_5 \ln x_5 \\ & + \beta_6 x_1 + \beta_7 x_2 + \beta_8 x_3 + \beta_9 x_4 + \beta_{10} x_5. \qquad (1)\end{aligned}$$

The translog functional form is another procedure often used for the estimation of production functions, in part because of its generality and in part because it has been found to result in a better fit than alternative forms (Guilkey, Lovell, and Sickles 1983). Although others (Clark 1989) are exploring the application of the translog form to issues in economic education, the translog was not tractable in our research because our aggregation of the student data into forty-six high school classes left us with too few observations to estimate the translog with precision.

In our implementation of DEA, we used the ratio model developed by Charnes et al. (1978, 1981) for making an efficiency analysis of DMUs. Following the earlier exposition of Charnes et al. (1978), as simplified for our case of a single output, DEA maximized for each DMU the ratio of the weighted output measure to the sum of the weighted input measures, subject to the constraint that the equivalent ratios for the other DMUs were less than or equal to unity. This nonlinear programming problem resulted in efficiency values for each DMU. Stated in symbols, the problem for the *k*th DMU was

$$\text{Max } h_k = uy_k / \sum_{i=1}^{m} v_i x_{ik} \tag{2}$$

subject to

$$uy_j / \sum_{i=1}^{m} vx_{ij} \le 1 \qquad j = 1, \ldots, n$$

$$u, v_i \ge 0 \qquad i = 1, \ldots, m$$

In this problem, y is the output, the x values are inputs of which there are m, and there are j DMUs. Charnes et al. (1978) have shown that the above nonlinear programming problem can be transformed into an ordinary linear programming problem. We used a Fortran code developed by Assad (1986, 3–4 and passim) to implement a version of the ratio model of DEA developed by Charnes et al.[2]

When DMUs are evaluated relative to other DMUs in the same program, *intraprogram* efficiency measures are obtained. The efficiency of a program can be evaluated by adjusting the inputs and output of the DMU to what they would be if the DMU was on its program frontier.[3] If the adjusted values are used, all the DMUs can be evaluated together. Any inefficiency that remains can be attributed to program inefficiency.

DATA

A brief description of the data set we used can be found in Baumol and Highsmith (1988). The data set was based on the responses to questionnaires at four levels: the school district, the school, the teacher, and the student. All the 3,266 students in the original sample took the Test of Economic Literacy (TEL). For details of the test, see Soper and Walstad (1987).

The output measure used in the analysis was the class average of the number of questions answered correctly on Form B of the TEL. The inputs included in the analysis were the sum of verbal and math SAT scores, the percentage of mothers of students in the class who graduated from college, the percentage of students in the class who were white, the percentage of students in the class who were male, and the percentage of students in the class who had taken an economics course (broadly defined). The SAT variable was included as a proxy for the students' academic ability. The mother's education variable was included both as a proxy for the student's academic ability and as a possible proxy for a home environment that was conducive to successful study. We conformed to standard practice in including race and gender control variables. We also considered using as inputs the number of years the teacher had taught, the number of credit hours the teacher had in economics, and the average annual expenditure per year per student in the district. None of these three variables was statistically significant in preliminary production function regressions. In addition, others (Blais and Greenwood 1989; Clark 1989) have found that a teacher's experience and college training do not appear to affect student performance in the NAEE data set, and Lopus (1989) has given good arguments for questioning the usefulness of including the measure of annual expenditure in the data set.

The subsample used in our study was restricted to include students for whom there were no missing values for any of the variables used in the preliminary analysis.[4] The subsample consisted of the 888 students who satisfied this restriction. Although the NAEE data has a rich array of variables, many of the observations have missing values for some of the important variables. If sample selection bias is suspected, the inverse Mill's ratio could be included in the estimation of the production functions, although the problems in identifying the inverse Mill's ratio are well known. It may also be possible to find or construct proxies for some of the missing variables (Little and Rubin 1987, 60–67). The use of such proxies may increase the efficiency of the estimates, but at the price of also increasing measurement error and, thereby, increasing the inconsistency of the estimates. In the end, we believed that the best remedy for the missing variable problem might be to test the robustness of our results by applying DEA to other economic education data sets such as the one described by Walstad and Soper (1988) and analyzed by Becker and Walstad (1990).

The 888 students in our final sample were members of fifty classes, twenty-four of which were in the DEEP program and twenty-six of which were not. Four classes were excluded from the analysis either because they had fewer than 6 students with nonmissing data (two classes) or because the students were in lower grades than the rest of the sample (two classes). The final data set consisted of data for twenty-three DEEP classes and twenty-three non-DEEP classes. (That balance was coincidental for our purposes—data envelopment analysis does not require an equal number of cases under each program.) The school districts in the DEEP sample were located in twelve states representing all areas of the United States: California, Connecticut, Illinois, Indiana, Maryland, Michigan, Missouri, New Jersey, New York, Ohio, South Carolina, and Texas. The non-DEEP districts were also located in twelve states: Alabama, Arkansas, California, Florida, Illinois, Iowa, Maryland, Michigan, New York, Ohio, Texas, and Washington. The definition of the variables used in the analysis, as well as some related variables of interest, are provided in Table 1. Because the aggregated data set was not large, we provide in Tables 2 and 3 complete data on the variables used in the analysis and, in Tables 4 and 5, complete data on some related variables of interest.[5]

RESULTS

Of the three functional forms that we estimated for the production function, the simple linear form fitted the data best (Table 6). In the linear regression, TEL scores were higher for those classes with higher average SAT scores, a larger percentage of whites, and a greater percentage of students who had taken an economics course. Although not significant at customary significance levels, the coefficients of the race and mother's education variables also had the expected positive signs.

In the DEA reported in Table 7, we estimated efficiency values for all forty-six high school classes, using the same input variables that were used as independent variables in the production functions (Table 6). Table 8 reports the residuals from the three production functions reported in Table 6 along with the efficiency values calculated in the DEA reported in Table 7. The data in Table 8 are usefully summarized by the correlation coefficients reported in Table 9. As alternative measures of efficiency, the three residual measures and the DEA efficiency ratio were all highly correlated with one another.

We proceeded to estimate the efficiency of DEEP classes relative to other DEEP classes and the efficiency of non-DEEP classes relative to other non-DEEP classes (see Table 10). When DEEP classes were evaluated relative to other DEEP classes, sixteen out of twenty-three were evaluated as efficient. Similarly, when non-DEEP classes were evaluated relative to other non-DEEP classes, ten out of twenty-three were evaluated as efficient.

Based on the results in the program-specific estimation, inputs for inefficient schools were adjusted to what they would have been if the schools had been on their program-specific frontiers. These adjusted values were then used to calculate interenvelope efficiency values (Table 11). When the input values were adjusted as described earlier, we found that nine of twenty-three DEEP classes were evaluated as efficient, and fourteen of twenty-three non-DEEP classes were evaluated as efficient (Table 11). The evidence thus indicated that the efficiency of some classes was improved by the presence of DEEP, but the efficiency of other classes seemed to be harmed by DEEP. Overall, the evidence was not favorable to DEEP. Although nine non-DEEP classes would have been more efficient if they had been in the DEEP program, fourteen DEEP classes would have been more efficient if they had *not* been in the DEEP program.

TABLE 1
Definition of Variables

DISTCODE	NAEE code number for school district. Each district was assigned a unique number within the state. The values 1 to 50 were used for DEEP districts and 51 to 99 for non-DEEP districts
TEL (27.3; 24.5)	Average total correct (out of 46 possible) for class. Test was Form B of the TEL
SUMSAT (864.6; 205.8)	Equal to sum of verbal and math SAT scores (or transformed ACT score where SAT not available)
COLGRAD (0.29; 0.21)	Percentage of mothers (of students in class) who graduated from college (father's COLGRAD status was used when mother's COLGRAD status was not available)
WHITE (0.83; 0.21)	Percentage of students in class who were white (not black, Hispanic, Asian, or other)
MALE (0.50; 0.21)	Percentage of students in class who were male
ECOCOURS (0.83; 0.33)	Percentage of students in class who had ever taken a course in economics (broad definition of taking a course included, e.g., "economics as part of another class, but not a separate unit")
ANNEXPEN (3827.48; 13.42)	District official's estimate of "the current total annual instruction expenditure per student (all grades) in your district"
ECOHRSTE (15.43; 15.58)	Teacher's total undergraduate and graduate hours in economics
SOMECOL (0.18; 0.10)	Percentage of mothers (of students in class) who attended college, but did not graduate (father's SOMECOL status was used when mother's SOMECOL status was unavailable)
SCHGRADE (94.78; 7.78)	Average student's current grade or year in school (100 = senior; 75 = junior; 50 = sophomore; 25 = freshman)
PRIVPUB (1.85; 0.36)	1 if school was private; 2 if public
URBAN (0.26; 0.44)	1 if school was in urban area; 0 if not
TOTYRTAU (16.13; 8.00)	The number of years that the teacher had taught school
HIGHGRADE (0.13; 0.13)	Percentage of mothers (of students in class) who graduated from high school but did not attend college (father's HIGHGRAD status was used when mother's HIGHGRAD status was not available)
ECNPER12 (54.93; 44.30)	District official's estimate of "the % of 12th grade students in your school district who take/took a course in the 12th grade focusing exclusively on economics" (may be a proxy for how seriously the school district takes economic education)

Note: The first number in parentheses is the variable mean; the second is the variable standard deviation. The data set consists of forty-six classes.

TABLE 2
Values for Output and Inputs for DEEP Classes

Class no.	State	DISTCODE	TEL	SUMSAT	COLGRAD	WHITE	MALE	ECOCOURS
1	Connecticut	51	33.80	1,169.20	0.84	0.92	0.56	1.00
2	California	51	27.00	672.80	0.20	1.00	0.60	1.00
3	California	52	21.43	878.19	0.29	0.29	0.76	1.00
4	Connecticut	51	30.22	1,084.44	0.65	0.87	0.44	1.00
5	Connecticut	51	27.52	1,150.38	0.67	0.86	0.62	0.95
6	Illinois	51	21.44	663.46	0.13	0.94	0.45	0.88
7	Indiana	52	18.88	813.75	0.00	0.75	0.56	1.00
8	Indiana	53	19.73	1,009.09	0.27	0.91	0.82	0.73
9	Indiana	53	16.44	918.50	0.13	0.81	0.19	0.06
10	Maryland	51	30.17	1,073.33	0.17	0.83	0.83	1.00
11	Michigan	52	25.33	875.58	0.71	0.58	0.58	1.00
12	Missouri	51	28.33	902.01	0.33	1.00	0.67	1.00
13	New Jersey	51	29.78	1,040.33	0.78	0.89	0.78	1.00
14	New Jersey	51	22.17	974.44	0.56	1.00	0.78	0.11
15	New York	51	25.89	1,087.35	0.22	0.89	0.67	1.00
16	New York	51	27.56	1,137.53	0.56	0.88	0.56	0.25
17	New York	53	26.57	1,080.00	0.57	1.00	0.29	1.00
18	Ohio	51	27.80	567.75	0.20	1.00	0.70	1.00
19	Ohio	51	19.29	692.75	0.18	0.94	0.47	0.06
20	Ohio	52	22.61	853.79	0.05	0.93	0.50	1.00
21	South Carolina	51	17.48	829.26	0.13	0.35	0.52	1.00
22	South Carolina	51	18.20	856.36	0.36	0.28	0.28	1.00
23	Texas	51	26.61	951.48	0.30	0.96	0.48	1.00

TABLE 3
Values for Output and Inputs for non-DEEP Classes

Class no.	State	DISTCODE	TEL	SUMSAT	COLGRAD	WHITE	MALE	ECOCOURS
24	Alabama	2	12.60	325.09	0.27	0.80	0.53	1.00
25	Alabama	2	8.43	275.48	0.14	0.71	0.43	0.00
26	Alabama	2	13.17	539.68	0.08	1.00	0.58	1.00
27	Alabama	3	17.75	753.28	0.08	0.92	0.58	0.92
28	Alabama	3	23.89	791.84	0.00	1.00	0.56	1.00
29	Texas	3	24.44	915.14	0.17	0.93	0.51	1.00
30	Arkansas	1	3.00	507.67	0.14	0.86	0.29	1.00
31	California	6	15.92	795.08	0.17	0.83	0.33	0.92
32	California	13	25.18	1,102.15	0.37	0.82	0.50	0.97
33	California	14	23.29	963.10	0.38	0.24	0.38	1.00
34	Florida	2	23.62	834.34	0.23	0.92	0.23	1.00
35	Illinois	2	26.10	1,094.68	0.38	0.91	0.62	1.00
36	Iowa	2	23.28	926.03	0.33	1.00	0.61	0.22
37	Iowa	2	23.00	626.00	0.29	1.00	0.59	0.24
38	Maryland	1	18.07	855.86	0.29	1.00	0.50	0.79
39	Michigan	3	30.94	1,014.86	0.28	1.00	0.22	1.00
40	New York	1	20.00	814.30	0.05	0.70	0.00	1.00
41	New York	1	14.00	765.50	0.30	0.50	0.00	1.00
42	New York	1	20.93	937.07	0.07	0.62	0.00	1.00
43	New York	2	17.10	794.45	0.00	0.78	0.80	0.98
44	Ohio	3	14.33	821.78	0.33	0.89	0.44	0.22
45	Texas	3	32.71	1,124.29	0.36	0.79	0.50	1.00
46	Washington	3	24.11	912.00	0.11	1.00	0.53	1.00

TABLE 4
Values for Related Variables for DEEP Classes

Class no.	ANNEXPEN	ECOHRSTE	SOMECOL	SCHGRADE	PRIVPUB	URBAN	TOTYRTAU	HIGHGRAD	·ECNPER12
1	14,500	54	0.00	76.04	1	0	3	0.00	0*
2	2,918	15	0.10	100.00	2	0	30	0.10	100
3	2,546	3	0.14	100.00	2	1	17	0.05	35
4	14,500	4	0.04	85.87	1	0	17	0.04	0
5	14,500	4	0.14	95.00	1	0	17	0.00	0
6	2,848	9	0.25	100.00	2	0	10	0.06	100
7	2,405	21	0.31	100.00	2	0	20	0.31	100
8	3,260	6	0.27	100.00	2	0	22	0.09	67
9	3,260	6	0.06	100.00	2	0	22	0.25	67
10	3,010	30	0.17	91.67	2	0	7	0.17	5
11	4,704	0	0.04	97.73	2	1	16	0.08	10
12	2,900	7	0.50	91.67	2	0	10	0.00	8
13	4,440	9	0.11	97.22	2	0	27	0.00	5
14	4,440	33	0.17	82.35	2	0	14	0.00	5
15	6,279	18	0.22	94.44	2	0	16	0.11	7
16	6,279	12	0.19	100.00	2	0	16	0.06	7
17	5,323	30	0.14	91.67	2	1	25	0.00	25
18	3,509	5	0.20	77.50	2	0	26	0.10	19
19	3,509	5	0.12	100.00	2	0	26	0.12	19
20	3,153	62	0.18	100.00	2	1	21	0.27	100
21	1,058	24	0.13	96.74	2	1	11	0.30	100
22	1,058	9	0.16	90.22	2	1	3	0.00	100
23	3,519	12	0.39	88.04	2	0	4	0.04	100

TABLE 5
Values for Related Variables for non-DEEP Classes

Class no.	ANNEXPEN	ECOHRSTE	SOMECOL	SCHGRADE	PRIVPUB	URBAN	TOTYRTAU	HIGHGRAD	ECNPER12
24	2,474	20	0.20	100.00	2	0	20	0.53	100
25	2,474	20	0.14	75.00	2	0	20	0.14	100
26	2,474	15	0.25	100.00	2	0	20	0.29	100
27	2,122	25	0.08	100.00	2	0	19	0.50	100
28	2,122	25	0.11	100.00	2	0	19	0.00	100
29	3,249	6	0.24	100.00	2	0	2	0.10	100
30	2,300	9	0.29	96.43	2	1	23	0.00	3
31	3,300	17	0.25	100.00	2	0	14	0.17	100
32	2,836	9	0.18	100.00	2	1	18	0.05	75
33	3,024	6	0.14	100.00	2	1	30	0.10	80
34	1,780	12	0.08	77.08	2	0	8	0.15	100
35	3,317	21	0.33	89.29	2	0	23	0.00	25
36	2,554	18	0.28	100.00	2	0	15	0.11	5
37	2,554	18	0.24	100.00	2	0	15	0.06	5
38	3,222	2	0.14	91.07	2	0	1	0.21	0
39	1,970	12	0.28	100.00	2	0	18	0.17	50
40	2,500	4	0.20	100.00	1	1	29	0.15	100
41	2,500	0	0.00	100.00	1	1	10	0.30	100
42	2,500	75	0.17	100.00	1	1	2	0.17	100
43	2,600	0	0.15	100.00	1	0	14	0.28	0
44	4,206	6	0.22	77.78	2	0	22	0.11	100
45	3,249	6	0.07	100.00	2	0	2	0.00	100
46	2,819	6	0.32	97.22	2	0	18	0.05	5

TABLE 6
Coefficient Estimates of Three Functional Forms for the Production Function

	Regression #1 (Linear)	Regression #2 (Cobb-Douglas)	Regression #3 (Transcendental)
	Dependent variables		
	TEL	ln (TEL)	ln (TEL)
	Independent variables		
Constant	−18.816 (−1.661)	−0.338 (−0.369)	4.755 (0.952)
SUMSAT	0.626 (5.050)	—	0.004 (0.222)
COLGRAD	0.147 (1.768)	—	0.002 (0.685)
WHITE	0.221 (2.481)	—	0.028 (1.791)
MALE	0.123 (1.387)	—	0.006 (1.741)
ECOCOURS	0.127 (2.272)	—	0.003 (1.147)
ln (SUMSAT)	—	0.900 (4.890)	0.623 (0.549)
ln (COLGRAD)	—	0.007 (0.403)	−0.003 (−0.136)
ln (WHITE)	—	0.132 (0.985)	−1.407 (−1.585)
ln (MALE)	—	0.015 (0.868)	−0.038 (−1.372)
ln (ECOCOURS)	—	0.003 (0.092)	−0.048 (−0.841)
N	46	46	46
R^2	.66	.48	.58

Note: t statistics appear in parentheses.

TABLE 7
Data Envelopment Analysis Efficiency Values for All Classes Estimated Together

DEEP classes			Non-DEEP classes		
Class no.	State	Efficiency value	Class no.	State	Efficiency value
1	Connecticut	.97	24	Alabama	.79
2	California	.96	25	Alabama	1.00
3	California	1.00	26	Alabama	.64
4	Connecticut	.93	27	Alabama	.72
5	Connecticut	.82	28	Alabama	1.00
6	Illinois	.91	29	Texas	.86
7	Indiana	1.00	30	Arkansas	.16
8	Indiana	.67	31	California	.64
9	Indiana	1.00	32	California	.78
10	Maryland	1.00	33	California	1.00
11	Michigan	.95	34	Florida	.90
12	Missouri	.87	35	Illinois	.77
13	New Jersey	.91	36	Iowa	.93
14	New Jersey	.97	37	Iowa	1.00
15	New York	.83	38	Maryland	.62
16	New York	1.00	39	Michigan	1.00
17	New York	.83	40	New York	1.00
18	Ohio	1.00	41	New York	.83
19	Ohio	1.00	42	New York	1.00
20	Ohio	.92	43	New York	.89
21	South Carolina	1.00	44	Ohio	.65
22	South Carolina	.89	45	Texas	1.00
23	Texas	.85	46	Washington	.88

TABLE 8
Efficiency Measures from Three Production Functions and from Data Envelopment Analysis

Class no.	Residuals from Regl	Residuals from Reg2	Residuals from Reg3	Effic. value from DEA
1	.23	.17	.15	.97
2	19.32	.45	.40	.96
3	8.58	−.02	−.13	1.00
4	1.99	.13	.16	.93
5	−8.73	−.02	−.06	.82
6	8.03	.24	.25	.91
7	−1.71	−.08	−.11	1.00
8	−15.16	−.23	−.36	.67
9	−6.40	−.33	−.19	1.00
10	12.84	.14	−.00	1.00
11	4.46	.15	.11	.95
12	8.81	.23	.16	.87
13	.02	.15	.04	.91
14	−6.16	−.08	−.20	.97
15	−3.00	−.03	−.09	.83
16	2.58	−.01	−.03	1.00
17	−10.24	.00	.10	.83
18	27.11	.64	.54	1.00
19	9.48	.09	.10	1.00
20	1.78	.06	.06	.92
21	.93	−.17	−.18	1.00
22	−1.13	−.16	−.07	.89
23	2.83	.12	.13	.85
24	−1.48	.36	.32	.79
25	6.08	.11	.11	1.00
26	−12.33	−.06	−.11	.64
27	−6.68	−.07	−.11	.72
28	7.92	.18	.15	1.00
29	1.67	.07	.07	.86
30	−38.24	−1.49	−1.41	.16
31	−13.78	−.23	−.16	.64
32	−6.53	−.07	−.06	.78
33	9.01	−.02	.03	1.00
34	2.33	.12	.24	.90
35	−6.27	−.03	−.07	.77
36	2.55	.01	−.03	.93
37	17.82	.36	.31	1.00
38	−15.42	−.17	−.17	.62
39	11.78	.21	.34	1.00
40	1.86	−.02	.19	1.00
41	−13.19	−.32	−.11	.83
42	−.11	−.10	.11	1.00
43	−6.26	−.16	−.29	.89
44	−15.66	−.36	−.34	.65
45	15.19	.17	.18	1.00
46	.29	.06	.05	.88

TABLE 9
Correlations of Efficiency Measures from Three Production Functions and from Data Envelopment Analysis

	Resid. Reg1	Resid. Reg2	Resid. Reg3	Effic. DEA
Resid. Reg1	1.000	.854	.831	.822
Resid. Reg2	.854	1.000	.956	.712
Resid. Reg3	.831	.956	1.000	.735
Effic. DEA	.822	.712	.735	1.000

Note: The higher number in each cell is the correlation coefficient. In a one-tailed test, each of the above correlations was statistically significant even at the stringent .001 level.

TABLE 10
DEEP and Non-DEEP Program Specific Efficiency Values

DEEP classes			Non-DEEP classes		
Class no.	State	Efficiency value	Class no.	State	Efficiency value
1	Connecticut	1.00	24	Alabama	1.00
2	California	1.00	25	Alabama	1.00
3	California	1.00	26	Alabama	.75
4	Connecticut	1.00	27	Alabama	.76
5	Connecticut	.86	28	Alabama	1.00
6	Illinois	1.00	29	Texas	.89
7	Indiana	1.00	30	Arkansas	.18
8	Indiana	.68	31	California	.66
9	Indiana	1.00	32	California	.78
10	Maryland	1.00	33	California	1.00
11	Michigan	1.00	34	Florida	.92
12	Missouri	.93	35	Illinois	.79
13	New Jersey	.94	36	Iowa	1.00
14	New Jersey	.97	37	Iowa	1.00
15	New York	.90	38	Maryland	.65
16	New York	1.00	39	Michigan	1.00
17	New York	1.00	40	New York	1.00
18	Ohio	1.00	41	New York	.83
19	Ohio	1.00	42	New York	1.00
20	Ohio	1.00	43	New York	.92
21	South Carolina	1.00	44	Ohio	.78
22	South Carolina	1.00	45	Texas	1.00
23	Texas	.99	46	Washington	.89

TABLE 11
Inter-Envelope Efficiency Values

DEEP classes			Non-DEEP classes		
Class no.	State	Efficiency value	Class no.	State	Efficiency value
1	Connecticut	.97	24	Alabama	.79
2	California	.96	25	Alabama	1.00
3	California	1.00	26	Alabama	.98
4	Connecticut	.93	27	Alabama	.99
5	Connecticut	.95	28	Alabama	1.00
6	Illinois	.91	29	Texas	.99
7	Indiana	1.00	30	Arkansas	.98
8	Indiana	.98	31	California	.93
9	Indiana	1.00	32	California	1.00
10	Maryland	1.00	33	California	1.00
11	Michigan	.95	34	Florida	1.00
12	Missouri	.94	35	Illinois	1.00
13	New Jersey	.97	36	Iowa	.93
14	New Jersey	1.00	37	Iowa	1.00
15	New York	.93	38	Maryland	.99
16	New York	1.00	39	Michigan	1.00
17	New York	.83	40	New York	1.00
18	Ohio	1.00	41	New York	1.00
19	Ohio	1.00	42	New York	1.00
20	Ohio	.92	43	New York	1.00
21	South Carolina	1.00	44	Ohio	1.00
22	South Carolina	.89	45	Texas	1.00
23	Texas	.86	46	Washington	.99

FUTURE WORK

In the future, it would be useful to test further the robustness of the analysis by applying it to additional data sets and by estimating the additive form of DEA, which has been described in Charnes et al. (1985). If the results prove robust, then it would be useful to learn the characteristics of the schools that benefit from DEEP and compare them with the characteristics of those that do not benefit from it. The techniques for this analysis are being developed in research by Rhodes and Southwick (1988, 1989).

It would also be interesting to evaluate programs other than DEEP. In particular, Rhine (1989) has concluded that whether a state chooses to mandate economic education matters much more for the economic literacy of students than whether the district participates in DEEP, indicating that it may be useful to compare the efficiency of high school classes in state-mandated vs. non-state-mandated programs.

NOTES

1. Only one output is currently used. Other outputs that might be added from the present data set are the students' attitude about economics and the students' perceptions about how much they learned and how useful the knowledge learned will be. Self-reported perceptions

are not traditionally held in high regard in economic analysis (McCloskey 1985, 181–82). Entering that controversy would distract us from our objective, which was to learn whether DEA is a useful technique for measuring the efficiency of DMUs and programs in economic education. As a result, we did not include any outputs in our study other than the test scores. When the Joint Council completes a follow-up survey of the students, additional "hard" measures of output will be available.

2. The Fortran code solved the following problem:

   MIN W
   subject to

$$\begin{array}{rrrrr} & Y\lambda - & s^{+} & & = Y_0 \\ X_0\theta - & X\lambda & & - & s^{-} = 0 \\ W - X_0\theta + & & \epsilon e^{T} s^{+} & + & \epsilon e^{T} s^{-} = 0 \\ & \lambda, & s^{+}, & & \text{and } s^{-} \geq 0, \end{array}$$

   where X_0 and Y_0 were, respectively, the input and output values for a DMU being evaluated; θ was the efficiency variable; s^{+} was a vector of output slacks; s^{-} was a vector of input slacks; ϵ was the non-Archimedean infinitesimal; λ was an $\mathbf{n} \times 1$ vector (where $\mathbf{n}$ was the number of DMUs) and e^{T} was a matrix of 1's of adequate dimension. The non-Archimedean infinitesimal is a function that approaches zero in the limit. Banker et al. (1989) suggest that the non-Archimedean infinitesimal may usefully be thought of as the reciprocal of the "big M" that is used in one common algorithm for solving linear programming problems (Chvatal 1983, 128). In actual calculations, some very small number is used for ϵ.
3. The adjusted input vector was equal to: $X_0 - s^{-}$. The adjusted output vector was equal to: $Y_0\theta + s^{+}$.
4. In addition, observations were excluded if the school district reported spending $100 or less per year per student on the grounds that these responses were miscoded or represented a misunderstanding of the question by the respondent. If SAT scores were missing but ACT scores were available, the ACT scores were converted into SAT equivalents. The formula for converting from ACT to SAT scores was estimated by Jim Clark using tables from the University of Illinois, University Office of School and College Relations, Research Memorandum 80-5, July 1980. The formula used was $\text{SUMSAT} = 430 + 2.94 * \text{ACT}^{1.662}$.
5. Because the data envelopment analysis program makes use of non-Archimedean infinitesimals and because of rounding conventions in the program, inputs and outputs must be scaled so that each variable varies roughly within the same range. In particular, we scaled the values of inputs so that they ranged in value from 0 to 100. Values of 0 were assigned a value of 0.001 to avoid division by 0. Because the efficiency values obtained from DEA are insensitive to the units in which outputs and inputs are measured, scales may be chosen for computational convenience (Assad 1986). The scaled values are not directly meaningful, so in Tables 2 through 5 the unscaled values are presented.

REFERENCES

Ahn, T., A. Charnes, and W. W. Cooper. 1988. A note on the efficiency characterizations obtained in different DEA models. *Socio-Economic Planning Sciences* 22 (6): 253–57.

Aigner, D., C. A. K. Lovell, and P. Schmidt. 1977. Formulation and estimation of stochastic production function models. *Journal of Econometrics* 6:21–37.

Assad, M. J. D. 1986. Data envelopment analysis software for microcomputers: CCR1, additive, minimax, summary window. Research Report CCS #538 (April). Center for Cybernetic Studies, University of Texas at Austin.

Banker, R., A. Charnes, W. W. Cooper, J. Swarts, and D. Thomas. 1989. An introduction to data envelopment analysis with some of its models and their uses. CCS Report #619 (February), Paper No. 1. Center for Cybernetic Studies, University of Texas at Austin.

Banker, R. D., and A. Maindiratta. 1988. Nonparametric analysis of technical and allocation efficiencies in production. *Econometrica* 56 (November): 1315–32.

Baumol, W. J., and R. J. Highsmith. 1988. Variables affecting success in economic education: Preliminary findings from a new data base. *American Economic Review: AEA papers and proceedings* 78 (May): 257–62.

Becker, W. E., and W. B. Walstad. 1990. Data loss from pretest to posttest as a sample selection problem. *Review of Economics and Statistics* 72 (February): 184–88.

Bessent, A. M., E. W. Bessent, A. Charnes, W. W. Cooper, and N. C. Thorogood. 1983. Evaluation of educational program proposals by means of DEA. *Educational Administration Quarterly* 19 (2) (Spring): 82-100.

Bessent, A., W. Bessent, J. Kennington, and B. Reagan. 1982. An application of mathematical programming to assess productivity in the Houston independent school district. *Management Science* 28 (December): 1355–67.

Blais, J., and D. Greenwood. 1989. The effects of teacher, student, and school characteristics on student achievement in economics. Preliminary draft. Rhode Island Council on Economic Education, Rhode Island College, Providence, R.I.

Brenneke, J. S., R. J. Highsmith, J. C. Soper, W. B. Walstad, and M. W. Watts. 1988. A research and evaluation agenda for DEEP and precollege economic education. *Journal of Economic Education* 19 (Winter): 5-13.

Charnes, A., W. W. Cooper, B. Golany, L. Seiford, and J. Stutz. 1985. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics* 30:91-107.

Charnes, A., W. W. Cooper, and E. Rhodes. 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research* 2:429–44.

Charnes, A., W. W. Cooper, and E. Rhodes. 1981. Evaluating program and managerial efficiency: An application of data envelopment analysis to program follow through. *Management Science* 27 (June): 668–97.

Charnes, A., and S. Zlobec. 1990. Stability of efficiency evaluations in data envelopment analysis. *Zeitschrift fur Operations Research*, Series A: Theory (forthcoming).

Chvatal, V. 1983. *Linear programming.* New York: W. H. Freeman and Company.

Clark, J. E. 1989. Using a translog production function to analyze input use in high school economics classes. Preliminary draft. Center for Economic Education, Department of Economics, Wichita State University, Wichita, Kans.

Farrell, M. J. 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society*, Series A, 120, part 3: 253–90.

Greene, W. H. 1980a. Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics* 13:27-56.

———. 1980b. On the estimation of a flexible frontier production model. *Journal of Econometrics* 13:101-15.

Grosskopf, S. 1986. The role of the reference technology in measuring productive efficiency. *Economic Journal* 96 (June): 499–513.

Guilkey, D. K., C. A. K. Lovell, and R. C. Sickles. 1983. A comparison of the performance of three flexible functional forms. *International Economic Review* 24 (October): 591–616.

Heath, J. A. 1989. An econometric model of the role of gender in economic education. *American Economic Review: AEA Papers and Proceedings* 79 (May): 226–30.

Intriligator, M. D. 1978. *Econometric models, techniques, & applications.* Englewood Cliffs, N.J.: Prentice-Hall.

Little, R. J. A., and D. B. Rubin. 1987. *Statistical analysis with missing data.* New York: John Wiley and Sons.

Lopus, J. 1989. Do additional expenditures increase achievement in the high school economics class? Preliminary draft. Center for Economic Education, California State University, Hayward, Calif.

McCloskey, D. N. 1985. *The rhetoric of economics.* Madison, Wisc.: The University of Wisconsin Press.

Miller, J. C. 1982. Technical efficiency in the production of economic knowledge. *Journal of Economic Education* 13 (Summer): 3-13.

Rhine, S. L. W. 1989. The effect of state mandates on student performance. *American Economic Review: AEA Papers and Proceedings* 79 (2) (May): 231-35.

Rhodes, E. L., and L. Southwick, Jr. 1988. Determinants of efficiency in public and private universities. Mimeo Research Report. University of Indiana School of Environmental and Public Affairs.

———. 1989. Comparison of university performance differences over time. Mimeo Research Report. University of Indiana School of Environmental and Public Affairs.

Soper, J. C., and W. B. Walstad. 1987. *Test of Economic Literacy: Second edition examiner's manual.* New York: Joint Council on Economic Education.

Walstad, W. B., and J. C. Soper. 1988. A report card on the economic literacy of U.S. high school students. *American Economic Review: AEA Papers and Proceedings* 78 (2) (May): 251–56.

OTHER WORKS

Banker, R. D., and R. C. Morey. 1986. The use of categorical variables in data envelopment analysis. *Management Science* 32 (December): 1613–27.

Becker, W. E. 1983. Economic education research: Part I, issues and questions. *Journal of Economic Education* 14 (Winter): 10–17.

Hansen, W. L. 1988. A research and evaluation agenda for DEEP and precollege economic education: A comment. *Journal of Economic Education* 19 (Winter): 14–16.

Saunders, P. 1988. A research and evaluation agenda for DEEP and precollege economic education: A comment. *Journal of Economic Education* 19 (Winter): 17–19.

Sexton, T. R. 1986. The methodology of data envelopment analysis. In *Measuring efficiency: An assessment of data envelopment analysis*, ed. R. H. Silkman, 7–29. New directions for program evaluation, no. 32, Winter. San Francisco: Jossey-Bass.

Sexton, T. R., R. H. Silkman, and A. J. Hogan. 1986. Data envelopment analysis: Critique and extensions. In *Measuring efficiency: An assessment of data envelopment analysis*, ed. R. H. Silkman, 73–105. New directions for program evaluation, no. 32, Winter. San Francisco: Jossey-Bass.

Thanassoulis, E., R. G. Dyson, and M. J. Foster. 1987. Relative efficiency assessments using data envelopment analysis: An application to data on rates departments. *Journal of the Operational Research Society* 38 (5): 397–411.

Reprinted from **Journal of Economic Education**, published by HELDREF PUBLICATIONS,
4000 Albemarle Street, N.W., Washington, D.C. 20016.